

Let $P = \{p_1, p_2, \dots, p_n\}$

$Q = \{q_1, q_2, \dots, q_n\}$ be 2 sets of corresponding points in \mathbb{R}^d

To find : rotation matrix R and translation vector t such that

$$F(R, t) = \underset{\substack{R \in SO(d) \\ t \in \mathbb{R}^d}}{\operatorname{argmin}} \sum_{i=1}^n w_i \|q_i - (Rp_i + t)\|^2$$

where w_i are weights for each point pair

To find t :

$$\frac{dF}{dt} = \sum_{i=1}^n 2w_i (Rp_i + t - q_i) = 0$$

$$2t \left(\sum_{i=1}^n w_i \right) + 2R \left(\sum_{i=1}^n w_i p_i \right) - 2 \sum_{i=1}^n w_i q_i = 0$$

$$\text{Taking } \bar{p} = \frac{\sum_{i=1}^n w_i p_i}{\sum_{i=1}^n w_i}, \quad \bar{q} = \frac{\sum_{i=1}^n w_i q_i}{\sum_{i=1}^n w_i}, \quad \text{we get}$$

$$t - \bar{q} + R\bar{p} = 0$$

$$\Rightarrow t = \bar{q} - R\bar{p}$$

Putting t into F ,

$$\begin{aligned} F(R, t) &= \sum_{i=1}^n w_i \|q_i - Rp_i - \bar{q} + R\bar{p}\|^2 \\ &= \sum_{i=1}^n w_i \|R(p_i - \bar{p}) - (q_i - \bar{q})\|^2 \end{aligned}$$

Restate problem with zero translation :

$$x_i = p_i - \bar{p}, \quad y_i = q_i - \bar{q}$$

Hence,

$$R = \underset{R \in SO(d)}{\operatorname{argmin}} \sum_{i=1}^n w_i \|R x_i - y_i\|^2$$

$$\begin{aligned} \text{Now, } \|R x_i - y_i\|^2 &= (R x_i - y_i)^T (R x_i - y_i) \\ &= (x_i^T R^T - y_i^T) (R x_i - y_i) \\ &= x_i^T R^T R x_i - y_i^T R x_i - x_i^T R^T y_i + y_i^T y_i \quad (\text{since } R^T R = I) \end{aligned}$$

$x_i^T R^T y_i$ is a scalar : $1 \times (d \times d \times d \times d) = 1 \times 1$
and hence is equal to its transpose.

$$\therefore x_i^T R^T y_i = (x_i^T R^T y_i)^T = y_i^T R x_i$$

$$\therefore \|R x_i - y_i\|^2 = x_i^T R^T R x_i - 2 y_i^T R x_i + y_i^T y_i$$

$$\therefore \underset{R \in SO(d)}{\operatorname{argmin}} \sum_{i=1}^n w_i \|R x_i - y_i\|^2$$

$$= \underset{R \in SO(d)}{\operatorname{argmin}} \left(\sum_{i=1}^n w_i x_i^T R^T R x_i - 2 \sum_{i=1}^n w_i y_i^T R x_i + \sum_{i=1}^n w_i y_i^T y_i \right)$$

$$= \underset{R \in SO(d)}{\operatorname{argmin}} -2 \sum_{i=1}^n w_i y_i^T R x_i$$

these are not dependent on R and do not matter while minimizing.

$$= \underset{R \in SO(d)}{\operatorname{argmax}} \sum_{i=1}^n w_i y_i^T R x_i$$

removing the scalar multiplication

Now, vectorising $\sum_{i=1}^n w_i y_i^T R x_i$, we get

$$\sum_{i=1}^n w_i y_i^T R x_i = \operatorname{tr}(W Y^T R X), \text{ where :}$$

$$W = \begin{bmatrix} w_1 & & & \\ & w_2 & & \\ & & \ddots & \\ & & & w_n \end{bmatrix}_{n \times n}$$

$$= \text{diag}(w_1, \dots, w_n)$$

$$Y = \begin{bmatrix} -y_1^T & & \\ & -y_2^T & \\ & & \ddots \\ & & & -y_n^T \end{bmatrix}_{d \times n}$$

$$X = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \dots & x_n \\ | & | & & | \end{bmatrix}_{d \times n}$$

" We need rotation R which maximizes $\text{tr}(WY^T R X)$.

$$\text{tr}(WY^T R X) = \text{tr}((WY^T)(R X)) = \text{tr}(R X W Y^T) \quad [\text{tr}(AB) = \text{tr}(BA)]$$

Let $d \times d$ covariance matrix $S = X W Y^T$. Taking SVD,

$$S = U \Sigma V^T$$

$$1. \text{tr}(R X W Y^T) = \text{tr}(R S) = \text{tr}(R U \Sigma V^T) = \text{tr}(\Sigma V^T R U)$$

Since V, R, U are orthogonal $\Rightarrow M = V^T R U$ is orthogonal.

\therefore For each column m_j of M , $m_j^T m_j = 1$.

Hence, all numbers m_{ij} are of magnitude ≤ 1 .

$$m_j^T m_j = 1 \quad \Rightarrow \quad \sum_{i=1}^d m_{ij}^2 = 1 \quad \Rightarrow \quad m_{ij}^2 \leq 1 \quad \Rightarrow \quad |m_{ij}| \leq 1$$

$$\therefore \text{tr}(\Sigma M) = \begin{bmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & \ddots \\ & & & \sigma_d \end{bmatrix} M = \sum_{i=1}^d \sigma_i m_{ii} \leq \sum_{i=1}^d \sigma_i$$

(where Σ is a diagonal matrix)
and $\sigma_1, \sigma_2, \dots, \sigma_d \geq 0$.

∴ To maximize $\ln(\Sigma M)$, $m_{ii} = 1$.

Since M is orthogonal \Rightarrow to maximize $\ln(\Sigma M)$, $M = I$.

$$\begin{aligned} \therefore M^T &= V^T R U^T = I & \Rightarrow V &= R U \\ & & \Rightarrow R &= V U^T \end{aligned}$$

Hence proved mathematically that Procrustes alignment gives the best aligning transform between point clouds with known correspondences.